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Online multi-step prediction for wind speeds and solar irradiation: Evaluation of prediction errors

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ABSTRACT

We propose a general method for predicting multiple steps ahead of our target system and estimating simultaneously the prediction errors in a real time. The requirement of the proposed method is that we have a time series of the target system. We demonstrate the method by artificial data, real wind speed data, and real solar irradiation data.

1. Introduction

Renewable energy should be installed more to reduce the CO_2 emission and overcome the oil depletion. However, if we introduce more renewable energy, the power grid system might be destabilized due to the fluctuations of weather conditions. To keep the power grid system stable even when we introduce more renewable energy to the power grid system, we need to predict the outputs of renewable energy and compensate the fluctuations by thermal power plants, hydroelectric power plants, and/or batteries. Identifying the uncertainty of future renewable energy outputs is a key to realize such compensations. Although there are many pieces of prediction work relying on numerical weather predictions, there is no method as far as we know that provides multi-step predictions and their uncertainty in a real time given a past time series of the target system [1,2]. Such a method is necessary when we would like to produce short-term predictions of renewable energy below 2 h [3].

We propose a method for predicting multi steps ahead of the target system as well as their uncertainties online given a past time series of the target system. Our method realizes such a method by extending our previous work [4], which is an extension of Kwasniok and Smith [5,6]. We demonstrate the proposed method using artificial datasets as well as wind speed data and solar irradiation data.

2. Methods

In this paper, we extend our previous work [4] for predicting multi-steps ahead online. Suppose that we can observe $s_t \in R$ and that we predict $s_{(t_1+p)}$ for $p = 1,2,\ldots,P$ given the observations of s_t up to $t \le t_1$. We assume that we know already an appropriate set of delays for delay coordinates $\vec{s}(t) = (s_t, s_{t-\tau}, \ldots, s_{t-\tau(d-1)})$, where τ is called a delay and d is the embedding dimension. At the beginning of the algorithm, we feed, into the database, the observed values until the database is filled. Here the database has B entries and each entry has $(d+P)$–dimensional elements, within which d elements correspond to the past and the current parts, and P elements correspond to the future part. (Namely, the database D is the $B \times (d+P)$ matrix.) Thus, we need to observe s_t $\{B + \tau(d-1) + P\}$ times to start its prediction.

After we start the prediction, at each time before we observe s_t, we predict s_{t+p-1} for $p = 1,2,\ldots,P$ by (1) finding the K nearest neighbors (let $n_k(t-1)$ be the time index for the k th nearest

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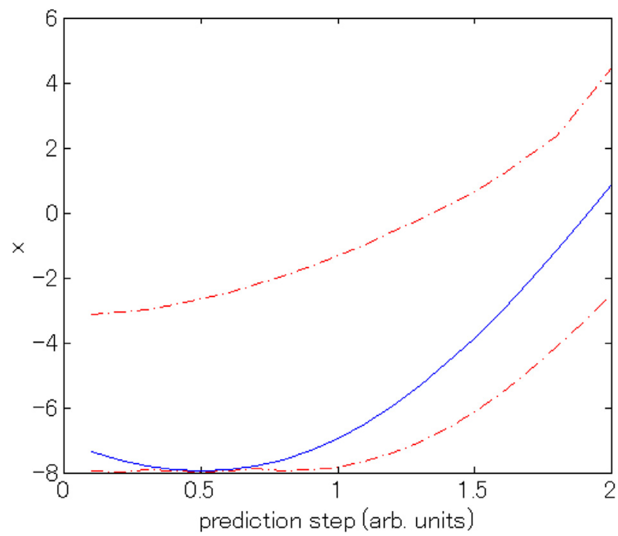

Fig. 1. The upper and lower bounds (red dotted lines) for 96% confidence intervals for the predicted time series (blue solid line), the Rössler model. Here, steps up to 20 steps head are predicted. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

neighbor for $k = 1,2,\ldots,K$) to $\vec{s}(t-1)$ from the past and current parts of the database, and (2) letting the ensemble $\{D(n_k(t-1), d+p), k = 1,2,\ldots,K\}$ as probabilistic prediction for p steps ahead. We may use the histogram of the ensemble for constructing the probabilistic prediction. We may use the mean and the standard deviation of the ensemble for evaluating the probabilistic prediction. After we observe s_t, we attempt to update the database. For this sake, we use the current database D to predict s_{t-P+p} from $(s_{t-P}, s_{t-\tau-P}, \ldots, s_{t-\tau(d-1)-P})$ for $p = 1,2,\ldots,P$. Let $\hat{s}_{t-P+p}$ be such prediction. The prediction error is $|\hat{s}_{t-P+p} - s_{t-P+p}|$ for $p = 1,2,\ldots,P$. Then, we randomly choose the bth entry of the database and swap the entry with the current data to prepare the temporary database $\overline{D}$, namely, $\overline{D}(i,j) = D(i,j)$ for $i \neq b$ and $\overline{D}(b,:) = (s_{t-P}, s_{t-\tau-P}, \ldots, s_{t-\tau(d-1)-P}, s_{t-P+1}, s_{t-P+2}, \ldots, s_t)$. Then, we

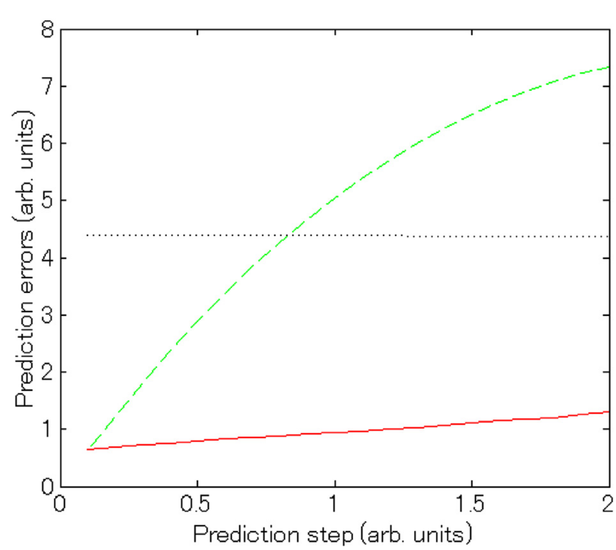

Fig. 2. Prediction errors for prediction by averaging ensembles (red solid line), persistence prediction (green dashed line), and mean prediction (black dotted line), in the case of Rössler model. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

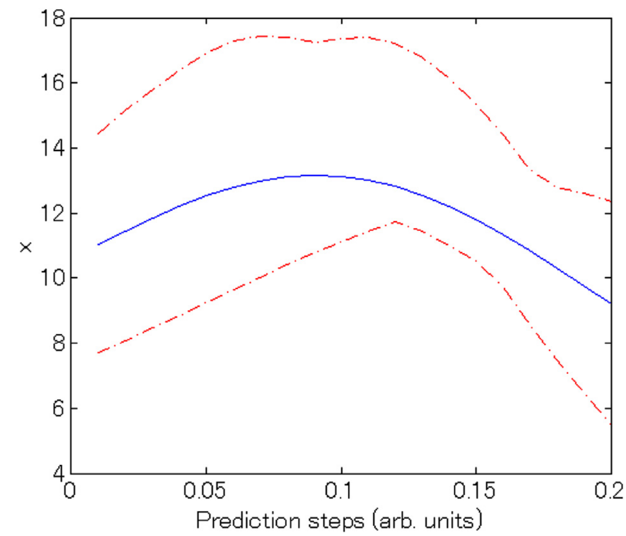

Fig. 3. Lower and upper bounds (red dashed lines) for 96% confidence intervals for the predicted time series (blue solid line), the Lorenz model. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

predict $D(b,(d+1):(d+P))$ from $D(b,1:d)$ using the database temporary database $\overline{D}$. Letting the prediction $\bar{s}_p$ for $p = 1,2,\ldots,P$, the prediction error is $|\bar{s}_p - D(b,d+p)|$ for $p = 1,2,\ldots,P$. When $|\bar{s}_p - D(b,d+p)| < |\hat{s}_{t-P+p} - s_{t-P+p}|$ for more than half of $p \in \{1,2,\ldots,P\}$, then we replace the current database D with the temporary database $\overline{D}$ and go back to the beginning of this paragraph.

The difference between the previous work [4] and the current work is that in the current work, we attempt to provide the probabilistic prediction while in the previous work [4], we simply provided the mean prediction.

3. Examples

Here, we show some examples. First, we apply the proposed method to two toy models, the Rössler model [7] and the Lorenz model [8], both of which are mathematical models of deterministic chaos.

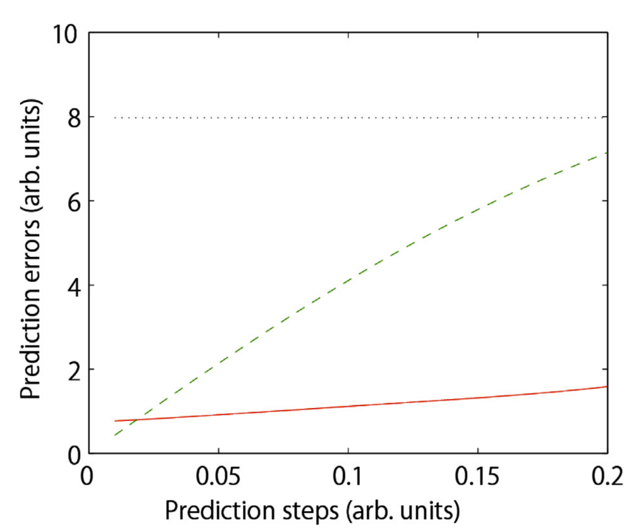

Fig. 4. The prediction errors for the prediction by taking ensemble average (red solid line), the persistence prediction (green dashed line), and the mean prediction (black dotted line), in the case of Lorenz model. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

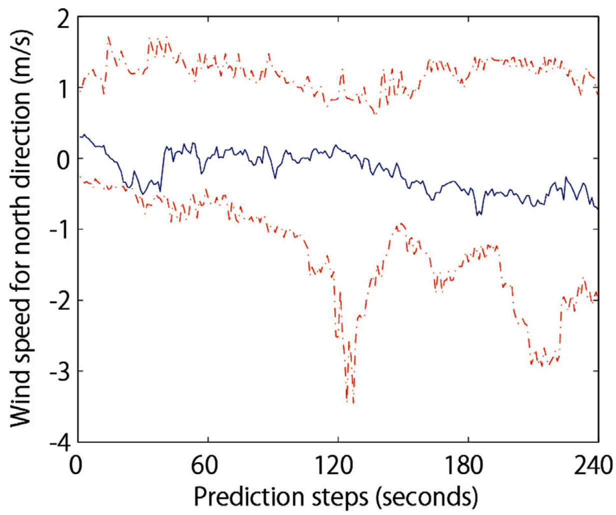

Fig. 5. The upper and lower bounds (red dashed lines) for 96% confidence intervals of the prediction for the actual value (blue solid line), the real wind data. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The Rössler model [7] is defined as follows:

$$\dot{x} = -(y+z),$$
$$\dot{y} = x + 0.36y,$$
$$\dot{z} = 0.4 + z(x-4.5).$$

We generated a scalar time series containing 10 000 points by observing x every 0.1 unit time. We used 20-dimensional delay coordinates to predict steps up to 20 steps ahead. We used 25 nearest neighbors to generate 96% confidence intervals of prediction. The size of database was 500.

The results are shown in Figs. 1 and 2.

In the most cases, the 96% confidence intervals contain the real values. The probability that the 96% confidence intervals contain the actual values is more than 99% for even prediction step up to 20 steps ahead.

When we calculated the prediction errors between the averages of ensembles and the predicted values, the prediction errors tended to be smaller than their climate alternatives, namely, the persistence prediction, where we let the current value be the prediction for the future, and the mean prediction, where we let the mean of the first half of the given time series be the prediction for the future.

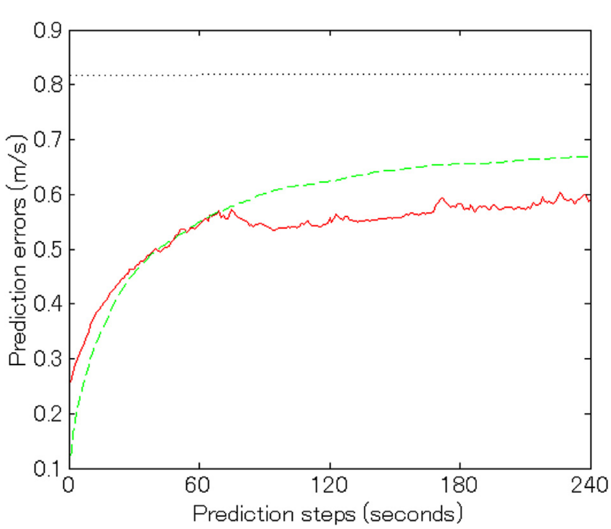

Fig. 6. The prediction errors for the prediction by taking ensemble averages (red solid line), the persistence prediction (green dashed lines), and the mean prediction (black dotted line). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

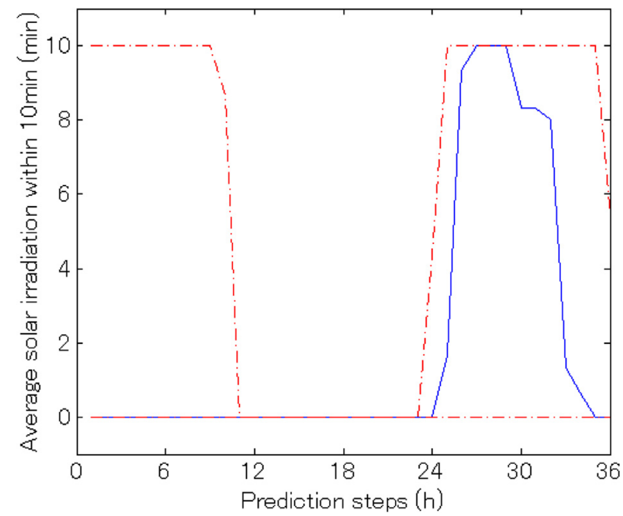

Fig. 7. An example of 92% confidence intervals (red dash-dotted lines) for predicting the actual value (blue solid line), the solar irradiation case. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

It took about 12 s to complete the calculation.

The Lorenz model [8] is defined as follows:

$$\dot{x} = 10(x-y),$$
$$\dot{y} = -xz + 28x - y,$$
$$\dot{z} = xy - \frac{8}{3}z.$$

We generated a one-dimensional time series containing 10 000 points by recording x every 0.01 unit time. We used 20 dimensional delay coordinates to predict steps up to 20 steps ahead. We used 25 nearest neighbors to construct 96% confidence intervals. The size of database was 500.

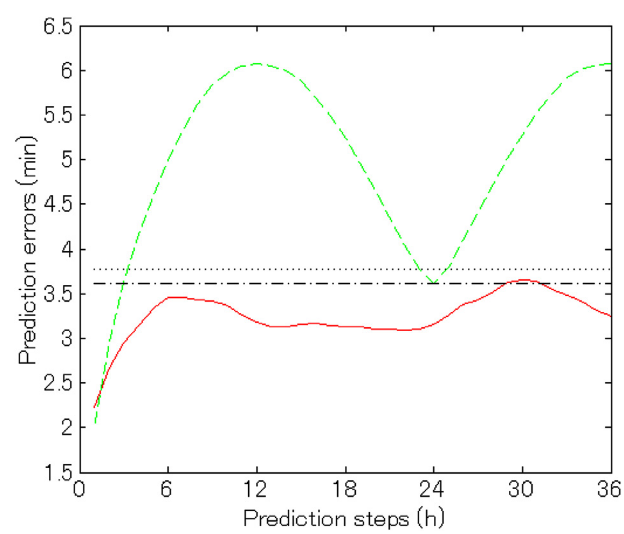

Fig. 8. The prediction errors by the prediction by the ensemble average (red solid line), the persistence prediction (green dashed line), the mean prediction (black dotted line), and the prediction using 1 day periodicity (black dash-dotted line), the solar irradiation case. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

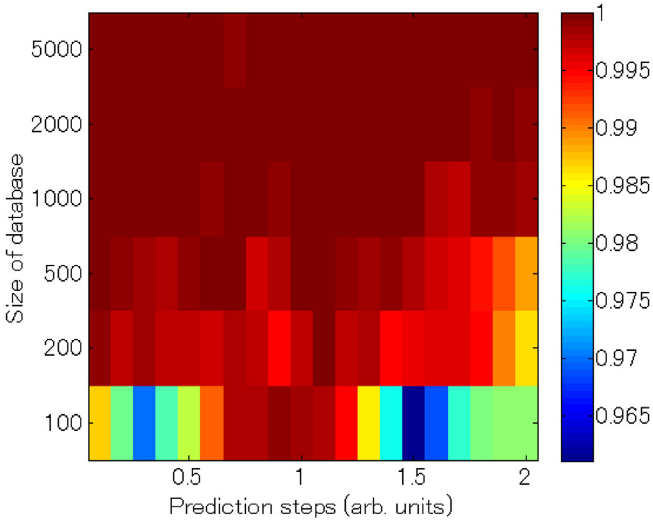

Fig. 9. The probability that 96% confidence intervals cover the actual values depending on the size of database, the case of Rössler model.

The results are shown in Figs. 3 and 4. The probability that the 96% confidence interval included the actual value was more than 99.9% for every prediction step. The prediction by taking ensemble averages is better than the persistence and the mean predictions for all the tested prediction steps except for the prediction step of 0.01, where the persistence prediction showed the smaller prediction error. It also took about 12 s to finish the calculation.

We also tested the proposed method with real datasets. The real datasets we use here are the wind speed data [4,9–12] and the solar irradiation.

The wind speed data were previously used in Refs. [4,9–12]. In these references, we learned that the wind speed has serial dependence and is nonlinear.

We used the measurements observed on 1 September 2005. The observation lasted for 1 day. We took the moving average by using the window of 1 s. We used 60-dimensional delay coordinates to predict steps up to 240 steps (4 min) ahead. We used 25 nearest neighbors to generate 96% confidence intervals for the prediction. We set the database size to 500.

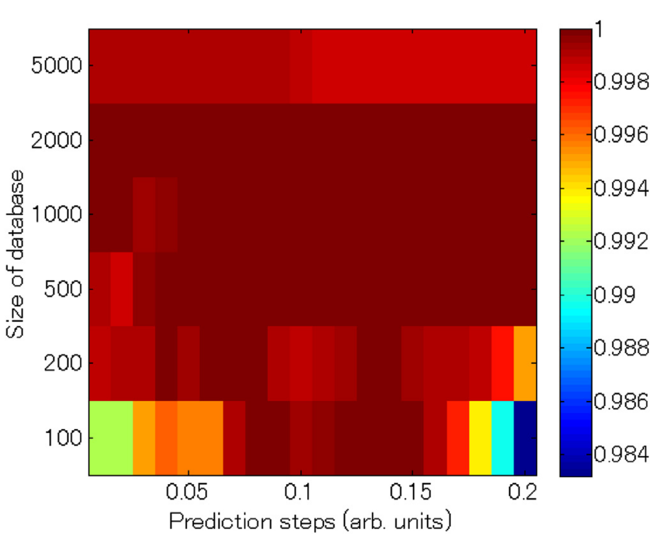

Fig. 10. The probability that 96% confidence intervals cover the actual values depending on the size of database, the case of Lorenz model.

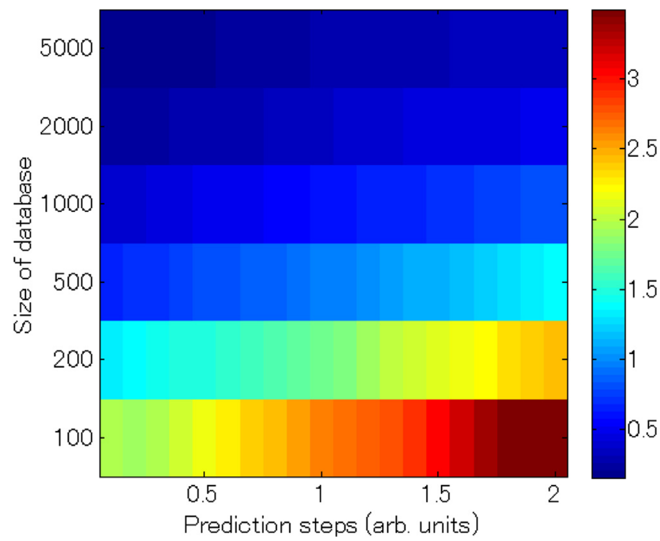

Fig. 11. The prediction errors of the ensemble average, depending on the size of database, the case of Rössler model.

The results are shown in Figs. 5 and 6. The 96% confidence interval contained the actual value at least more than or equal to 98.4% times for all the prediction steps. The prediction by the ensemble average achieved the smaller prediction error than the persistence prediction when the prediction step was more than 70 s.

It took 1277 s to complete the calculation. Therefore, the calculation can be done online.

The dataset of the solar irradiation was provided by the Japan Meteorological Agency. We chose the point of Fuchu-Shi, Tokyo, Japan. We extracted the measurements between 2002 and 2006. In the measurements, the solar irradiation was recorded as the total length of time the sun lit the ground during a specific time window of 10 min. Because the observation was made every 10 min, we took the moving average over 1 h. We used 36 dimensional delay coordinates to predict steps up to 36 steps (1.5 days) ahead. We chose 12 nearest neighbors to construct 92% confidence intervals. We set the size of database to 2000.

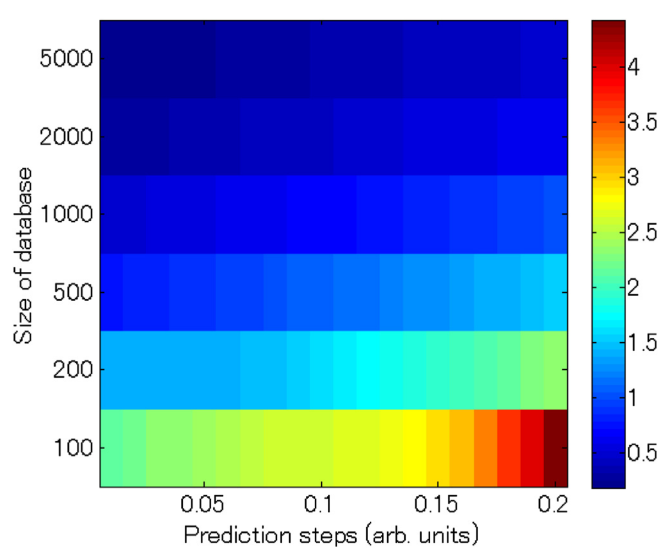

Fig. 12. The prediction error of the ensemble average, depending on the size of database, the case of Lorenz model.

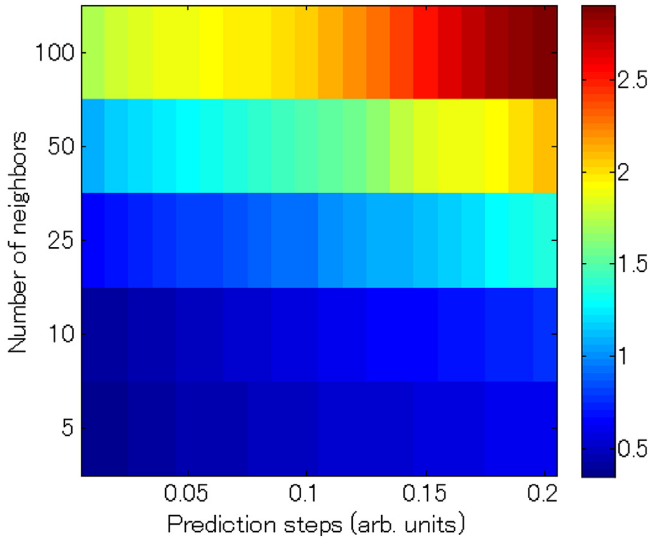

Fig. 13. The prediction error of the ensemble average, depending on the number of neighbors, the case of Rössler model.

The results are shown in Figs. 7 and 8. The 92% confidence intervals contained the real values more than or equal to 99.7% of time. Particularly, even if we had a cloudy day, the next sunny day's solar irradiation was predicted (Fig. 7). The prediction by the ensemble average was better than the persistence prediction, the mean prediction, and the prediction using 1 day periodicity when the prediction step was between 2 and 28 h (Fig. 8). The calculation took 420 s.

4. Discussions

We evaluate the dependence of the proposed method on parameters, namely, the size of database, and the number of nearest neighbors. Here, we use the datasets generated from the Rössler model and the Lorenz model used in Section 3.

First, we checked how the probability that the 96% confidence intervals cover the actual values changes depending on the database size. See the results in Figs. 9 and 10 for the examples of the Rössler model and the Lorenz model, respectively. We found that if the size of database is greater than or equal to 500, the probability that 96% confidence intervals cover the actual values is more than 96%, looking fine.

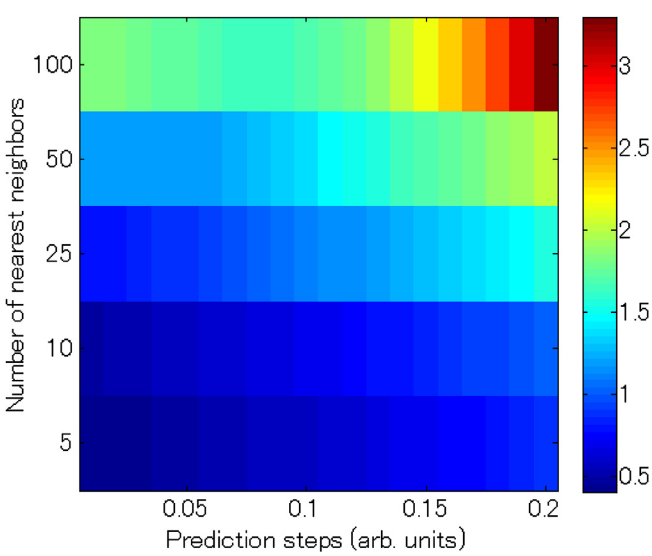

Fig. 14. The prediction error of the ensemble average, depending on the number of nearest neighbors, the case of Lorenz model.

Second, we checked how the prediction error changes depending on the size of database, while fixing the number of nearest neighbors. See Figs. 11 and 12 for the examples of the Rössler and the Lorenz models, respectively. We found that the prediction error becomes smaller if the size of database becomes larger.

Third, we examined how the prediction error changes depending on the number of neighbors. See Figs. 13 and 14 for the examples of the Rössler and the Lorenz models, respectively. We found that the prediction error gets smaller when we decrease the number of ensembles.

Our second and third discussions imply that making the size of neighbors smaller is an important factor for making the prediction error smaller. Therefore, there is a trade off between how fast we can predict the future and how accurately we can predict the future.

5. Conclusions

We have proposed a method for predicting the multi-steps ahead online given a scalar time series of target system. The method also provides the information on how much the prediction is reliable by using 96% or 92% confidence intervals. The method is an extension of Kwasniok and Smith [5]. We demonstrated the method using the artificial data and real datasets of wind and solar irradiation. We hope that the proposed method help to introduce more renewable energy into power grid systems. Each parameter of the proposed method should be chosen by considering the trade off between how fast we can predict the future and how accurately we can predict the future.

Acknowledgments

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